

# Proceedings of **2<sup>nd</sup> ICSIIT 2010**

International Conference on  
Soft Computing, Intelligent System  
and Information Technology

1-2 July 2010, Bali, Indonesia



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## **Proceedings**

# **International Conference on Soft Computing, Intelligent System and Information Technology 2010**

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**Publisher:**

Informatics Engineering Department  
Petra Christian University

ISBN: 978-602-97124-0-7

Additional copies may be ordered from:

Informatics Engineering Department  
Petra Christian University, Siwalankerto 121-131, Surabaya 60236, Indonesia

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# Comparison of Random Gaussian and Partial Random Fourier Measurement in Compressive Sensing Using Iteratively Reweighted Least Squares Reconstruction

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## ABSTRACT

Compressive sensing is the recent technique of data acquisition where perfect reconstruction of signal can be made from far fewer samples or measurement than traditional Shannon-Nyquist sampling theorem. Iteratively reweighted least squares (IRLS) reconstruction is a compressive sensing reconstruction algorithm which is a first-order approximation to the  $p$ -norm minimization where  $0 \leq p \leq 1$ . In this paper, We compare the random Gaussian and partial random Fourier (using Discrete Cosine Transform) measurement to encode signal and then reconstruct the signal using IRLS algorithm for various  $p$ . From the numerical experiments, random Gaussian and partial random Fourier measurement, both give better perfect reconstruction probability for  $p < 1$ . Also both of them give almost the same perfect reconstruction probability as function of sparsity and measurement number, just slightly different for some of  $p$  value.

## Keywords

Compressive sensing, IRLS, random Gaussian measurement, partial random Fourier measurement, perfect reconstruction probability, sparsity number, measurement number.

## 1. INTRODUCTION

Conventional approaches to sampling signal is using Shannon-Nyquist theorem : the sampling rate must be at least twice the maximum frequency in the signal (the so-called Nyquist rate) [1]. Compressive sensing (CS) is a sensing/sampling paradigm that goes against Shannon-Nyquist theorem. CS asserts that one can recover certain signals and images from far fewer samples or measurements than Shannon-Nyquist theorem use [2],[3]. Some potential applications are remote sensing [4], medical imaging [5], and sensor networks [6]. Three main issues in CS are sparsity of signal, CS measurement (Encoding) and CS reconstruction (Decoding). In this paper, signal will be considered sparse in time domain that contain a certain sparsity number which is number of non zero sample in signal. Random Gaussian and partial random Fourier matrices will be used to encode the signal. Both measurement will be compare by measuring the perfect reconstruction probability using Iteratively Reweighted Least Squares (IRLS) algorithms that was proposed in [7], [8].

## 2. IRLS ALGORITHMS

Consider an  $M \times N$  measurement matrix  $\Phi$ , where  $M < N$ , is used to encode signal  $x$ , result  $y = \Phi x$ , the vector of  $M$  measurements of

an  $N$  dimensional signal  $x$ . One of widely known reconstruction algorithm is minimum  $\ell_1$  norm reconstruction :

$$\min_{x'} \|x'\|_1, \text{ subject to } \Phi x' = y \quad (1)$$

If measurement matrix,  $\Phi$ , is random Gaussian distributed, there is a constant  $C$  such that if the sparsity of  $x$  has size  $K$  and  $M \geq CK \log(N/K)$ , then the solution to (1) will be exactly  $x' = x$  [9], [10]. In [7] and [8] propose that  $\ell_1$  can be replaced with the  $\ell_p$  norm, where  $0 < p < 1$ .

$$\min_{x'} \|x'\|_p^p, \text{ subject to } \Phi x' = y \quad (2)$$

In the case  $p < 1$ , IRLS can be used to for solving (2) by a replace the  $\ell_p$  objective function in (2) by a weighted  $\ell_2$  norm [11]:

$$\min_{x'} \sum_{i=1}^N w_i x_i'^2, \text{ subject to } \Phi x' = y \quad (3)$$

The Eq. (2) can be written as :

$$\min_{x'} \sum_{i=1}^N \left| x_i^{(n-1)} \right|^{p-2} x_i'^2, \text{ subject to } \Phi x' = y \quad (4)$$

where the weights,  $w$ , are computed from previous iterate  $x^{(n-1)}$ , so that the objective in (3) is a first-order approximation

to the  $\ell_p$  objective :  $w_i = \left| x_i^{(n-1)} \right|^{p-2}$ . The solution of (3)

can be given explicitly, giving the next iterate  $x^{(n)}$  [8]:

$$x_i^{(n)} = \Phi_n^T \left( \Phi_n \Phi_n^T \right)^{-1} y \quad (5)$$

where  $Q_n$  is the diagonal matrix with entries

$1/w_i = \left| x_i^{(n-1)} \right|^{2-p}$ . Using a small  $\varepsilon > 0$  to regularize the optimization problem,  $w_i$  become:

$$w_i = \left| x_i^{(n-1)} \right|^2 + \varepsilon^{\frac{p}{2}-1} \quad (6)$$

### 3. NUMERICAL EXPERIMENTS

The Eq. (5) will be solved numerically using various parameters of sparsity number  $K$ , number of measurement  $M$  using random Gaussian that is set to be orthonormal and partial random Fourier matrices (in this paper using Discrete Cosinus Transform (DCT) matrices) and  $p$ . The fix sample number  $N$  of signal  $x$  is 500 that has the sparsity number  $K$  which is chosen randomly with values 1 or -1 from a Gaussian distribution and using the sign function. Every experiment using certain parameters will be repeated 100 times to measure the perfect reconstruction probability.  $\varepsilon$  is initialized to 1 and  $x^{(0)}$  initialized to the minimum 2-norm solution of  $\Phi x' = y$ . The iteration (5) with  $w_i$  as in (6) is run until the change in relative 2-norm from the previous iterate is less than  $\frac{\sqrt{\varepsilon}}{50}$ , at which point  $\varepsilon$  is reduced by a factor 10, and the iteration

repeated beginning with the previous solution. This process is continued through a minimum  $\varepsilon$  of  $10^{-5}$ . The reconstruction is said to be perfect if mean squared error between  $x$  and  $x'$  less than  $10^{-3}$ . In this paper, we are considering  $0 \leq p \leq 1$ .

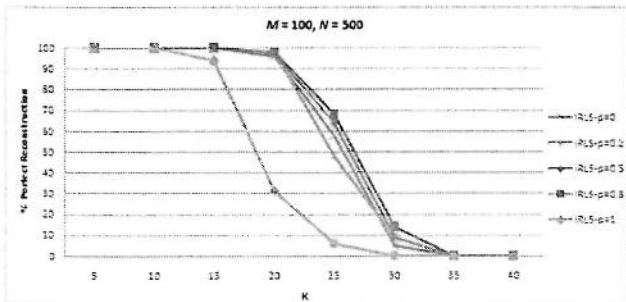


Figure 1. Perfect reconstruction probability as a function of  $K$  using random Gaussian measurement.

Figure. 1 shows the perfect reconstruction probability using random Gaussian measurement as a function of  $K$  for  $M = 100$  (20 %),  $p = 0, 0.2, 0.5, 0.8$ , and 1. We can see for  $p < 1$  give better result than  $p = 1$ , where for  $p < 1$  perfect reconstruction can achieve

100 % until  $K = 20$  while for  $p = 1$  just until  $K = 10$ , after that decay more quickly than  $p < 1$  and reach 0 % perfect reconstruction when  $K = 30$ . For  $p < 1$  give almost the same results but the best is at  $p = 0.8$ , and for all reach 0 % perfect reconstruction when  $K = 35$ .

Fig. 2 shows the perfect reconstruction probability using random Gaussian measurement as a function of  $M$  in ratio of measurement numbers ( $RMN$ ) =  $(M/N) \times 100$  % for  $K = 10$ ,  $p = 0, 0.2, 0.5, 0.8$ , and 1. We can see again for  $p < 1$  give better result than  $p = 1$ , where for  $p < 1$  perfect reconstruction can achieve 100 % at  $MNR = 14$  % while for  $p = 1$  need until  $MNR = 18$  %. For  $p < 1$  give almost the same results but the best is again at  $p = 0.8$ , and for all reach 100 % perfect reconstruction when  $MNR = 18$  %.

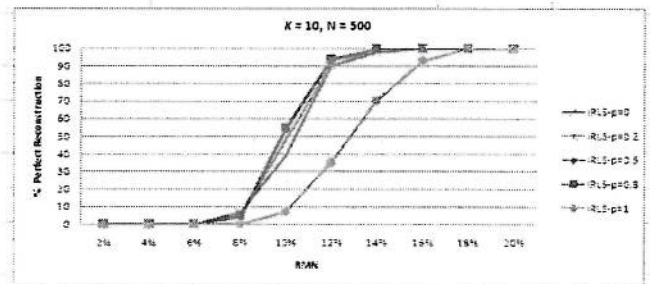


Figure 2. Perfect reconstruction probability as a function of  $RMN$  using random Gaussian measurement.

Figure. 3 shows the perfect reconstruction probability using partial random DCT measurement as a function of  $K$  for  $M = 100$  (20 %),  $p = 0, 0.2, 0.5, 0.8$ , and 1.

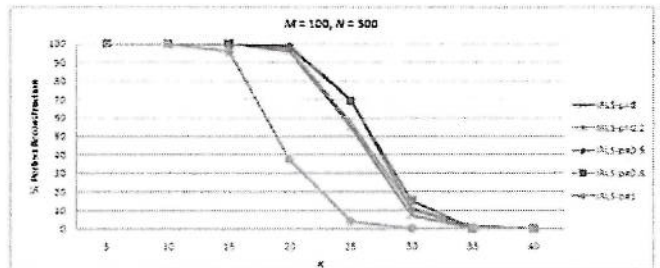


Figure 3. Perfect reconstruction probability as a function of  $K$  using partial random DCT measurement.

Figure. 4 shows the perfect reconstruction probability using partial random DCT measurement as a function of  $RMN$  for  $K = 10$ ,  $p = 0, 0.2, 0.5, 0.8$ , and 1.



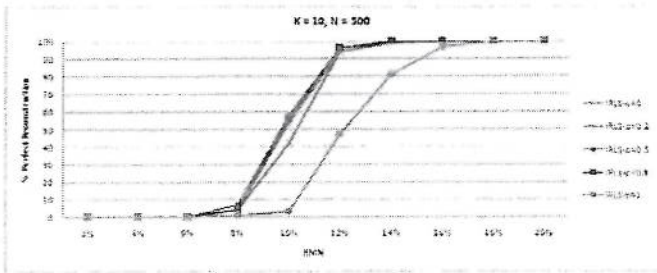


Figure 4. Perfect reconstruction probability as a function of  $RMN$  using partial random DCT measurement.

From Figure. 3 and 4, we can see that partial random DCT measurement give almost the same results as random Gaussian measurement. Although from Fig. 5, We can see that for  $p = 0.2$  and 1, partial random DCT give slightly better perfect reconstruction probability as a function of  $K$  than random Gaussian measurement.

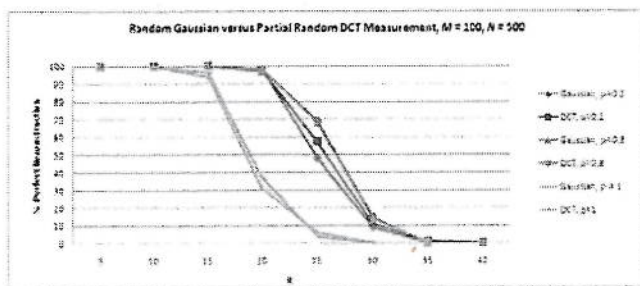


Figure 5. Comparison of perfect reconstruction probability as a function of  $K$  using random Gaussian and partial random DCT measurement.

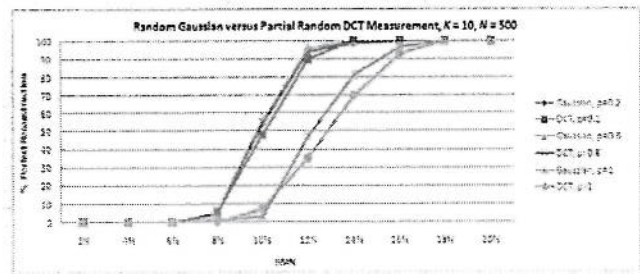


Figure 6. Comparison of perfect reconstruction probability as a function of  $RMN$  using random Gaussian and partial random DCT measurement.

From Figure. 6, We can see for perfect reconstruction probability as a function of  $RMN$ , the random Gaussian give better result than partial random DCT measurement for  $p = 1$ .

#### 4. CONCLUSIONS

From the results above, We can conclude that random Gaussian and partial random Fourier (DCT) measurement, both give better perfect reconstruction probability for  $p < 1$ . Also both of them give almost the same perfect reconstruction probability as function of  $K$  and  $RMN$ , just slightly different for some of  $p$  value.

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